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A Path Planning Method Based on Multi-Objective Cauchy Mutation Cat Swarm Optimization Algorithm for Navigation System of Intelligent Patrol Car

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ABSTRACT The intelligent patrol car with environmental sensing and autonomous navigation is a special robot, which is mostly used for equipment defect detection in industrial areas such as the power distribution room or data center room. A path planning algorithm for the navigation system of intelligent patrol car is proposed to ensure efficient and secure navigation in the complex indoor environment, and its effect is verified by simulation and experiment. First, a patrol car platform integrated with several intelligent devices is built to achieve global localization, mapping and path planning. Then a new co-optimization on multi-objective Cauchy mutation cat swarm optimization (MOCMCSO) and artificial potential field method (APFM) is proposed to solve the multi-objective optimization problem on shortest global path length and minimum total turning-angle variation. The optimal path is written into the navigation module to drive the patrol car to move and navigate. The simulations are carried out to confirm that the method can achieve a balance between the shortest path and good path smoothness, which has less optimization time and lower fitness value compared with multi-objective cat swarm optimization (MOCSO) and multi-objective particle swarm optimization (MOPSO), and is more suitable for global path planning in indoor environment. Finally, the experiments have been carried out in the data center equipment room to verify the effectiveness and superiority over the path planning algorithm on MOCMCSO.

INDEX TERMS Intelligent patrol car, path planning, simultaneous localization and mapping, Cauchy mutation cat swarm algorithm, multi-objective optimization.

I. INTRODUCTION

The intelligent patrol car for industrial applications is a special highly intelligent autonomous robot, which can be used for automatic inspection for high-voltage power distribution rooms, large data center equipment rooms and manufacturing workshops, and so on [1]. In recent years, the rapid development of artificial intelligence technology has driven the technological progress of autonomous robots in the fields of

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industrial internet, advanced manufacturing and unmanned detection [2], [3]. The high intelligent autonomous robots, such as patrol cars, service robots and rescue robots, have been widely applied to terrain detection, disaster relief and factory operations. These robots have brought huge benefits for enterprises and the industry [4].

The environmental perception, behavior control, navigation planning and dynamic decision are the necessary capabilities of intelligent patrol cars, to realize movement safely in indoor environment, on the one hand, the intelligent patrol car needs to sense the environmental information and its own posture through sensors [5], [6], on the other hand, it needs to process the perceived information and make the right decision for behavior control and finally move without collision towards the target point, which is path planning technology [7]. Recently, domestic and overseas scholars have taken up large-scale research on path planning algorithm, and achieved some excellent results [8], [9].

Due to the large number of electrical and communication equipment in industrial scenes, obstacle avoidance algorithms are required to have high real-time, robustness, and stability [10]. Intelligent patrol cars need to avoid collisions with high-risk and expensive equipment in large spaces quickly in order to reach the work area. The global path must be efficient, so path planning methods for complex indoor environments are key research direction. At present, the traditional algorithms of intelligent robot path planning include simulated annealing algorithm, artificial potential field method (APFM) and fuzzy logic algorithm, and so on [11], [12], the heuristic algorithm includes A*algorithm, Dijkstra algorithm and Floyd algorithm [13]–[15], graphic algorithm includes free-space algorithm, grid algorithm, visual graph algorithm and topology algorithm, and so on [16], intelligent bionic algorithm includes ant colony algorithm, genetic algorithm, particle swarm optimization algorithm, and so on [17]-[20].

A novel path planning method for intelligent patrol car is presented in this paper. Firstly, an intelligent patrol car platform based on the robot operating system (ROS) is built to realize the global localization, map-building and path planning. The system environment of intelligent patrol car platform also includes OpenCV [21] and TensorFlow [22] installed. Then, this paper focuses on the efficiency improvement of global path planning, a collaborative optimization method on MOCMCSO and APFM is proposed to find the global optimal path in indoor environment. Finally, the simulation test and actual machine experiment are executed to verify the superiority of the proposed algorithm compared with several other artificial intelligence methods.

II. GLOBAL PATH PLANNING

The intelligent patrol car obtains its own position, posture and environmental information through various sensors, and transforms the detected information into the information that can be analyzed by artificial intelligence models. The optimal global path is calculated by relevant algorithms.

A. WORKING PRINCIPLE

In autonomous navigation of mobile robots, global path planning is the process of planning a collision-free optimal path from a starting point to a target point based on known information about the operating environment [23]. The global path is composed of line segments between the sub target point and path discontinuity point. The patrol car will move along these lines to reach target during navigation stage. In addition to the shortest total length of the path, the criteria for judging the optimal path also includes indicators such as path smoothness and safety [18]. In particular, the operating space in the indoor environment is very limited. The optimal path must consider reducing the adjacent points of the path with large rotation angle. Best smoothness should also be considered when the path length is shortest.

In this paper, the artificial potential field method and twodimensional grid method are combined for the environment modeling. The grid method is a widely used environment modeling method, which decomposes the running space of the patrol car into a series of grid cells with binary information. The representation method of two-dimensional grid for environment modeling is shown in Fig. 1(a). Once the shape, size and location information of obstacles is identified, the grid with obstacles is set as obstacle grid, that is, gray, and the grid without obstacles is set as free grid, that is, white. Among them, the expanded grid combination of the obstacles is taken as the obstacle area, and the expanded radius is set on the chassis radius of intelligent patrol car, so that the patrol car can be moved as a particle, and the movement path is a series of connected free grids. The rectangular coordinates of grid are expressed as (x, y), and each grid is marked with the serial number T from 0, T = x+10y. During the movement process, the combined potential field generated by obstacles and targets for the patrol car is calculated as the potential field strength of the current grid T. The patrol car divides the whole map into several sub maps and constantly searches for the grid with the lowest potential field strength in sub maps. The line between these grids forms an accessible path, and the grid with the highest potential field strength in a large range is an obstacle.

B. ARTIFICIAL POTENTIAL FIELD METHOD

Artificial potential field method is a virtual force method for real-time obstacle avoidance planning for mobile intelligent agents. It regards both the target and obstacles that can produce the acting force as the force source. The target point creates attraction to the intelligent agent, on the contrary, the obstacles produce repulsive force, and thus the agent operation environment can be abstracted as an artificial potential field. Under the action of the resultant force, a smooth path far away from the obstacles is obtained by searching the direction of potential field falling. In this paper, the gradient potential field method is adopted to find the direction of potential field is used to represent the virtual force of agent in the environment, as shown in Fig. 1(b).

The location coordinate of the intelligent patrol car is expressed as [x,y], and that of the obstacle and target are $[x_i,y_i]$ and $[x_g,y_g]$ respectively. *i* is the obstacle number, when multiple obstacles appear, their coordinates are expressed as $[x_1,y_1], [x_2,y_2], \ldots, [x_i,y_i]$. The gravity of patrol car is directly proportional to the distance to the target, and the repulsive force is inversely proportional to the distance to the obstacle. The *q* represents the repulsive force parameter of the obstacle,



(a) Representation method for two-dimensional grid map



FIGURE 1. Experimental environment modeling.

and *g* represents the attraction parameter of the target point. The function model of obstacle repulsion field is as follows:

$$\Phi(q) = \begin{cases} \frac{1}{2}\eta \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 & \rho < \rho_0 \\ 0 & \rho > \rho_0 \end{cases}$$
(1)

where ρ is the distance between patrol car and obstacle, ρ_0 is the action distance of the obstacle that is a representation of range of obstacle repulsive force, the patrol car is not affected by the repulsive force of the obstacle when $\rho > \rho_0$, η is the gain coefficient of the repulsive force.

The negative gradient of repulsion field is set as repulsive force, and its function model is:

$$F(q) = -\nabla\Phi(q) = \frac{\eta}{\rho^2} \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right) \left[\frac{\partial\Phi}{\partial x}, \frac{\partial\Phi}{\partial y}\right]$$
(2)

The repulsive force is:

$$|F(q)| = \begin{cases} \frac{\eta}{\rho^2} \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right) & \rho < \rho_0 \\ 0 & \rho > \rho_0 \end{cases}$$
(3)

According to (3), the repulsive force of the patrol car is inversely proportional to the distance from the obstacle.

The attraction potential field of the target to the patrol car is as follows:

$$\Phi(g) = \frac{1}{2}\varepsilon \left[(x - x_g)^2 + (y - y_g)^2 \right]$$
(4)

where ε is the attractive force gain coefficient.

The negative gradient of attraction potential field is set as attraction force, and the function model is:

$$F(g) = -\nabla\Phi(g) = -\varepsilon \left[(x - x_g), (y - y_g) \right]$$
(5)

The attraction force is:

$$|F(g)| = \varepsilon \sqrt{(x - x_g)^2 + (y - y_g)^2}$$
(6)

 $F(q_i)$ represents the repulsive force produced by the ith obstacle, as shown in the Fig. 1(b), $F(q_1)$ is the repulsive force of obstacle 1, and $F(q_2)$ is the repulsive force of obstacle 2.

The artificial potential field of a certain point in the map is the sum of the attraction potential field on the target point and the repulsion potential field on the obstacle. The expression is as follows:

$$\Phi = \Phi(g) + \Phi(q) \tag{7}$$

The resultant force of the patrol car at a point in the map consists of the resultant force of attraction for target point and repulsion for obstacle, the expression is as follows:

$$F = -\nabla\Phi = F(g) + F(q) \tag{8}$$

If the repulsive force generated by obstacle and the attraction generated by the target reach a balance at a certain place, especially near the target point, it is easy to cause the problem of unreachable target. In this paper, the method on changing the repulsive force in potential field is adopted to change the repulsion potential field function. The expression is as follows:

$$\Phi(q) = \begin{cases} \frac{1}{2} \eta \left(\frac{1}{\rho} - \frac{1}{\rho_0}\right)^2 \cdot \left[1 - e^{-\frac{(x - x_g)^2 + (y - y_g)^2}{R^2}}\right] & \rho < \rho_0 \\ 0 & \rho \ge \rho_0 \end{cases}$$
(9)

where R is the radius of chassis, the closer the patrol car is to the target, the less repulsion it receives. Finally, the repulsion returns to zero at the target point, thus, the problem that the target near the obstacle is cannot be reachable can be solved.

C. MULTI-OBJECTIVE CAT SWARM OPTIMIZATION ALGORITHM

In the multi-objective optimization problem, each objective function represents one type of optimization strategy for a specific dimension, which may have cross and restriction relationship with each other, therefore, there is usually not an optimal solution for all objectives, but a set of Pareto optimal solutions [24]. The curve containing all the Pareto-optimal solutions is defined as Pareto-optimal front, which is a ball of radius. According to the Pareto advantage ranking method, Pareto optimal solution is obtained to archive in an external container, and the optimal solution set can be determined by comparing the external optimal solution with the current solution [25].

Classical cat swarm optimization (CSO) algorithm is a global optimization method which imitates the natural behavior of cats, and has shown the advantages in solving accuracy and convergence speed compared with other intelligent algorithms. The multi-objective cat swarm optimization (MOCSO) algorithm is a multi-objective version of the classical CSO algorithm. As a new evolutionary computing method, the MOCSO algorithm has some unique advantages: simple and easy to implement, convenient parameter adjustment, and high optimization accuracy. At present, it has been widely used in function optimization, neural network training, fuzzy system control and other intelligent multiobjective problem solving [26]–[30].

Cats are focused on hunting and catching moving prey, even during breaks, moving slowly to seek potential hunting opportunities. This behavior is called "seeking mode". After targeting prey, the cat quickly increases its speed and uses a great deal of energy to capture the moving prey. This behavior is called "tracing mode". The seeking mode improves the global search ability, while the tracking mode improves the search efficiency and precision. According to the mixture ratio (*MR*), the cats are assigned patterns to determine which cats are in seeking mode and which cats are in tracking mode [31].

The significant parameters of MOCMCSO include: PMO (Probability of Mutation Operation), CDC (Counts of Dimensions to Change), SMP (Seeking Memory Pool), and SRD (Seeking Range of the Selected Dimension).

The solution space is *i*-dimensional. In the *t*-th iteration, $x_{k,i}^*(t)$ is the position of *k*th cat in *i*th dimension, $v_{k,i}^*(t)$ is velocity vector. The global optimal position is $x_{g,i}^*(t)$. According to *MR*, the cats are randomly assigned to the ranks of seeking mode and tracing mode.

The steps of MOCSO algorithm can be detailed as follows:

1) SEEKING MODE

Step 1. Initialize the parameters of MOCMCSO, and generate the *K*-copy backup information of the *K* cat based on SMP. Initialize the position and velocity of cats in *i*-dimensional space.

Step 2. Select one of the *K* copies of the cat, maintain the current position, and mutate the rest of the copy (K - 1) under the influence of mutation operator. The dimension of each of the K - 1 copies is randomly mutated by adding or subtracting SRD to the parent individual. $x^*_{k,i}(t)$ represent the initial population.

Step 3. Calculate the fitness value of the *K*-copy backup of the *k*-th cat.

Step 4. The position of the optimal cat is calculated based on the fitness value of each cat, and is stored in an external container as Pareto optimal solution. Step 5. Based on SMP, the position of Pareto optimal solution is compared with that of current cat, and the solution with better fitness value is used to replace the current position.

2) TRACING MODE

In tracing mode, the motion direction of each cat at the next moment depends on the speed of the cat and the optimal position in cats. The algorithm flow is:

Step 1. The dimension in solution space is *i*. The speed vector of the *k*-th cat in the (t + 1)-th iteration $v_{k,i}^*(t + 1)$ can be expressed as:

$$v_{k,i}^{*}(t+1) = w * v_{k,i}^{*}(t) + c * r * (x_{g,i}^{*}(t) - x_{k,i}^{*}(t))$$
(10)

where w is the inertia weight value, c is acceleration constant. r is a random number between [0,1], it adopts the uniform distribution and the probability density function is same as (12). In the external container, the initial global optimal position $x_{g,i}^*(t)$ is assigned by the optimal solution of artificial potential field method.

Step 2. A cat moves quickly and tracks its prey. After each movement, the new position information of the k-th cat is calculated as follows:

$$x_{k,i}^*(t+1) = x_{k,i}^*(t) + v_{k,i}^*(t+1)$$
(11)

Step 3. If the new position of the k-th cat in any dimension exceeds the search range, the speed vector of the cat is set as the boundary value and the reverse search is performed.

Step 4. Evaluate the fitness value of each cat in the population.

Step 5. The final Pareto optimal solution set can be determined based on the value of fitness function, and the corresponding value is output.

D. MULTI-OBJECTIVE CAUCHY MUTATION CAT SWARM OPTIMIZATION ALGORITHM

The mechanism on updating population position does not fully consider the information of other optimal cats, so the classical MOCSO is unable to ensure the population diversity and may gradually fall into the local optimum [32]. This paper introduces a multi-objective Cauchy mutation cat swarm algorithm (MOCMCSO), which introduces Cauchy mutation operators to improve the performance of search patterns [33], expand the range of swarm search, and continuously improve population information during the seeking process to avoid premature convergence and localization optimal solution, fundamentally improve population diversity.

Cats are distributed to seeking mode and tracing mode according to a linear mixture ratio (MR_L) .

$$MR_{\rm L} = MR_{\rm max} - (MR_{\rm max} - MR_{\rm min}) * \frac{t}{IT_{\rm max}}$$
(12)

where the MR_{max} and MR_{min} are the maximum value and minimum value of MR, t is the current number of iterations and IT_{max} is the maximum number of iterations.

The steps of MOCMCSO algorithm can be detailed as:

1) SEEKING MODE

Step 1. Initialize the parameters of MOCMCSO, and generate the *K*-copy backup information of the *K* cat based on SMP.

Step 2. One among *K* copies maintains the present position and the rest (K - 1) copies carry out the mutation process under the influence of Cauchy mutation operator. Cauchy mutation can generate a large random number interval, which improves the search range of the cats, thus avoiding falling into the local optimal solution and improving the global convergence ability. $x^*_{k,i}(t)$ represent the initial population, the new individuals produced by Cauchy mutation are $x^*_{k,i}(t)$, the expression is:

$$x^{*,}{}_{k,i}(t) = x^{*}{}_{k,i}(t) + \sigma * C(0,1)$$
(13)

where C(0, 1) is a random number between 0 and 1, and adopts the uniform distribution, its probability density function is:

$$f(x^*) = \left\{ \begin{array}{l} \frac{1}{\mathbf{b} - a} \ a < x < b\\ 0 \ else \end{array} \right\}$$
(14)

The mutation value in the current dimension is set as the standard deviation $\sigma * C(0, 1)$.

Step 3. Calculate the fitness value of the K-copies.

Step 4. The position information of the optimal cat is calculated and stored in an external container as Pareto optimal solution.

Step 5. Based on SMP, the best copy among K copies from Pareto optimal solution is chosen and the position of kth cat is replaced by the position of the best copy.

2) TRACING MODE

The tracing mode process of the MOCMCSO is remains unchanged as the tracing mode process of classical MOCSO. If the termination condition of the MOCMCSO is not reached, the optimization process will continue and the global optimal solution can be output finally.

3) SIMULATION TEST ON MOCMCSO

The Cauchy mutation operator is introduced in the seeking process to enhance the global search ability of the MOCM-CSO algorithm. Simulation study is carried out in MATLAB to demonstrate the optimization capability of MOCMCSO for complex multi-objective optimization problem. The MOCSO and MOPSO is introduced for comparison with MOCMCSO on standard test functions as in Table 1. The initialization parameters for MOCMCSO and MOCSO are as follows: SMP = 2.8, SRD = 0.15, CDC = 75%, MR = 0.65, C = 2, w = 0.5, the archive size = 100, *r* is in [0,1], the maximum iteration number is sett as 500. The initialization parameters for MOPSO are: the archive size = 100, the inertia weight = 0.25, the acceleration constant = 3.5, the random number is in [0,1]. These parameters are the same in the three test

TABLE 1. Test function expressions.

Function
 Expression

 Test
function 1

$$\begin{cases} \min f_1(x, y) = (x^2 + y^2)^{\frac{1}{p}}, \\ \min f_2(x, y) = ((x - 0.5)^2 + (y - 0.5)^2)^{\frac{1}{p}}, x \in [-5, 10] \end{cases}$$

 Test
function 2

$$\begin{cases} \min f_1 = x_1, \\ \min f_2 = 1 - (\frac{f_1}{g})^2, g = 1 + \frac{9}{n - 1} \sum_{i=2}^n x_i, n = 30, x_i \in [0, 1] \end{cases}$$

 Test
function 3

$$\begin{cases} \min f_1 = x_1, \\ \min f_2 = 1 - (\frac{f_1}{g})^2, g = 1 + \frac{9}{n - 1} \sum_{i=2}^n x_i, n = 30, x_i \in [0, 1] \end{cases}$$

 Test
function 3

$$\begin{cases} \min f_1(x) = \begin{cases} -x, ifx \le 1, \\ -2 + x, if1 < x \le 3, \\ 4 - x, if3 & x \le 4, \\ -4 + x, ifx & >4, \\ \min f_2(x) = (x - 5)^2, x \in [-5, 10] \end{cases}$$

 TABLE 2. Comparison of MOCMCSO with MOCSO, MOPSO on all the three test functions.

Parameter	MOCMCSO	MOCSO	MOPSO							
Test function 1										
$\operatorname{Min} f_1(x)$	0.8750	0.9170	0.9068							
$\operatorname{Min} f_2(x)$	0.0013	0.0029	0.0037							
Computation time (s)	0.085	0.091	0.088							
	Test function 2									
$\operatorname{Min} f_1(x)$	0.0000e+241	0.0000e+256	0.0000e+252							
$\operatorname{Min} f_2(x)$	-1.5804e+248	-7.7113e+250	-2.6928e+250							
Computation time (s)	2.294	2.388	2.125							
Test function 3										
$\operatorname{Min} f_1(x)$	1.472	0.915	1.653							
$\operatorname{Min} f_2(x)$	1.960	4.544	3.962							
Computation time (s)	0.023	0.029	0.026							

functions, and the results obtained from 20 independent simulations based on the MOCMCSO, MOCSO and MOPSO are recorded and the best average result is shown in Table 2. All of the test function $1\sim3$ contain two objective functions $f_1(x)f_2(x)$, to solve the minimum. The position of the cats is initialized firstly, and then calculated by the two objective functions to obtain Pareto-optimal solutions.

All of MOCMCSO, MOCSO and MOPSO can achieve global optimization, compared with the MOCSO and MOPSO, the MOCMCSO performs better with respect to minimum solution on $f_1(x) f_2(x)$, and the computation time is relatively shorter. Through the Cauchy mutation operator is used to mutate the position of individuals to avoid premature convergence, which increases the diversity of the cats, and achieves excellent results in the classical test function, so MOCMCSO reflects the advantages for global convergence, and is very suitable for solving complex multiobjective problems.

E. CO-OPTIMIZATION OF APFM AND MOCMCSO

An APFM and MOCMCSO co-optimization algorithm is proposed in this section. The initial path is generated by APFM as the initial optimal position in cats, and then the MOCMCSO algorithm is used to iteratively find the optimal path, which can reduce the convergence time and make the cat swarm quickly approach the global optimal solution. The path planned by APFM and MOCMCSO co-optimization algorithm is expressed as $\{N_0, N_1, N_2, N_3, \dots, N_g\}$, N_0 and N_g are the starting point and the target point in the path. The line segment connecting N_0 with N_g as the X' axis of the new coordinate axis, a new coordinate system X'OY' is established with N_0 as the origin, and the conversion equation between the new coordinate and the original coordinate is as follows:

$$\begin{bmatrix} x'\\ y' \end{bmatrix} = \begin{bmatrix} \cos\varphi & -\sin\varphi\\ \sin\varphi & \cos\varphi \end{bmatrix} \begin{bmatrix} x\\ y \end{bmatrix} + \begin{bmatrix} x_{N_0}\\ y_{N_0} \end{bmatrix}$$
(15)

where φ is the angle between the new coordinate axis X' and the original coordinate axis X, the X axis in the new coordinate is M_0M_g , divided into i + 1 equal parts with the vertical line, and the target point M_g is also expressed as M_{i+1} , the crossover point of the vertical line and the original coordinate represents the optimal path $[M_0, M_1, M_2, M_3, \dots, M_g]$, the length is:

$$L_M = \sum_{j=0}^{l} \sqrt{(x'_{M_j} - x'_{M_{j+1}})^2 + (y'_{M_j} - y'_{M_{j+1}})^2}$$
(16)

The new vertical coordinate system and path points is shown in Fig. 2, The sum of the horizontal axis distance is a constant. The optimal distance in global path planning is to find the optimal solution set in the space of $y'_{Mj}(j = 1, 2, ..., i)$, the path sequence $[M_0, M_1, M_2, M_3, ..., M_i]$ is set as the initial optimal position in cats, each path from M_0 to M_g is represented as an vector in *i*-dimension $P_n = [x_{n1}, x_{n2}, x_{n3}..., x_{ni}]$. After the conversion from original coordinates to new coordinates, the goal is to find the optimal cat with the minimum distance sum between two adjacent points on the path.



FIGURE 2. Schematic diagram of new vertical coordinate system and path points.

The scene in this paper is the indoor data center equipment room, the smoothness and safety of the path must be taken into account. The patrol car should be as far away from the obstacles as possible, and the angle between the two adjacent path segments should be as large as possible. The angle of direction change required by the patrol car is smaller, and the smoothness of path is higher. The angle between the two adjacent path segments is $\delta = |\beta - \alpha|, \alpha$ is the angle of the previous path segment, β is the angle of the last path segment, the total turning-angle variation in the global environment can be obtained as follows:

$$\Omega = \sum_{j=1}^{i} \left| \arctan \frac{y'_{M_{j+1}} - y'_{M_{j}}}{x'_{M_{j+1}} - x'_{M_{j}}} - \arctan \frac{y'_{M_{j}} - y'_{M_{j-1}}}{x'_{M_{j}} - x'_{M_{j-1}}} \right| \quad (17)$$

Therefore, the shortest global path length and the minimum total turning-angle variation are set as two objective functions for path planning algorithm on MOCMCSO. The evaluation for Pareto optimal solution needs to avoid over close to the optimal solution of any single objective function and reflect the constraints and restrictive relation between the two objective functions. The multi-objective function can be expressed as:

$$\begin{cases} \operatorname{Min} f_{1}(x) = L_{M} = \sum_{j=0}^{i} \sqrt{(x'_{M_{j}} - x'_{M_{j+1}})^{2} + (y'_{M_{j}} - y'_{M_{j+1}})^{2}} \\ \operatorname{Min} f_{2}(x) = \Omega = \sum_{j=1}^{i} \left| \arctan \frac{y'_{M_{j+1}} - y'_{M_{j}}}{x'_{M_{j+1}} - x'_{M_{j}}} - \arctan \frac{y'_{M_{j}} - y'_{M_{j-1}}}{x'_{M_{j}} - x'_{M_{j-1}}} \right| \end{cases}$$

$$(18)$$

The algorithm process of APFM and MOCMCSO cooptimization is shown in Fig. 3, such as the following:

Step 1. The population is initialized, *k* is the number of the cats, *n* is the population number. Each individual in cats is represented as a set of vector representing the path. $P_k = [y'_{k,M1}, y'_{k,M2}, \dots, y'_{k,Mj}, \dots, y'_{k,Mi}], (k = 1, 2, \dots, n), (j = 1, 2, \dots, i)$. Initialize the position y^0_{kMj} and speed v^0_{kMj} of cats on each dimension.

Step 2. The global optimal path $[M_0, M_1, M_2, M_3, ..., M_g]$ is obtained by APFM as the initial value of the optimal solution for the subsequent MOCMCSO algorithm, the fitness value can be calculated based on (18) and stored in an external container as Pareto optimal solution.

Step 3. In the seeking mode of MOCMCSO, the K-1 copy of the *i*th cat is updated with the Cauchy mutation operator as (13), *t* is the iteration number. The Pareto optimal solution is compared with the updated cat's position, and the solution with better fitness value is regarded as the updated global optimal position.

In the tracking mode of MOCMCSO, The fitness value of the optimal solution $g_{k,best}(t)$ in the current *t*-th iteration of the *k*-th cat is calculated and compared with the fitness value of the optimal solution $g_{k,best}(t-1)$ stored in the external container. The $g_{k,best}(t)$ with better fitness value are set as the global optimal solution, otherwise the iteration will continue. Finally, the Pareto optimal solution set $g_{k,best}(t)$ can be obtained in the *t*-th iteration through the fitness evaluation, $g_{k,best}(t) = [y_{k,M1}(t), y_{k,M2}(t), \dots, y_{k,Mj}(t), \dots, y_{k,Mi}(t)],$ (k = 1,2,..., n, j = 1,2,..., i).

with the expressions as follows:



FIGURE 3. APFM and MOCMCSO co-optimization algorithm process.

Step 4. Check the termination condition, whether the maximum number of iterations is reached, if so, the algorithm process ends.

Step 5. The Pareto optimal solution set is output as global path, otherwise, repeat steps 2 to 4, and the algorithm continues to iterate.

F. FITNESS FUNCTION SELECTION

The output of MOCMCSO is a set of Pareto optimal solutions, any point on the Pareto curve represents a path scheme on multi-objective optimization for global path length and total turning-angle variation, but only one set of value can be input into the navigation module of intelligent patrol car. Therefore, the value at the midpoint of Pareto curve is selected as the optimal path based on the actual situation. At this time, the weighting ratio about the global path length and the total turning-angle variation is 1:1, representing that the importance on the shortest path length is the same as that of the minimum turning-angle variation.

The two objective functions are (18), respectively. Since the global path length and the total turning-angle variation are not in the same order of magnitude, they are normalized

$$nor\underline{L}_{M} = \frac{L_{M}^{k}}{\sum_{k=1}^{n} L_{M}^{k}}$$
(19)

(10)

$$nor_{\Omega} = \frac{\frac{\Delta L}{n}}{\sum_{k=1}^{n} \Omega^{k}}$$
(20)

$$f_{nor}(x) = 0.5^*(nor_L_M) + 0.5^*(nor_\Omega)$$
 (21)

By normalizing the two objective functions and setting them to equal weights, they can be transformed into a single objective function $f_{nor}(x)$, which is the sum of the normalized values of the two objective functions with equal weight. Thus, the comprehensive evaluation on global optimal solution by two objective functions is solved. The global path with 50% of the shortest path length and 50% of the minimum total turning-angle variation is selected as global optimal value and transferred to the ROS navigation module of intelligent patrol car.

III. SIMULATION RESEARCH

In this section, the simulation test on the APFM and MOCM-CSO co-optimization algorithm is carried out, and then the MOCSO and MOPSO algorithm are introduced with APFM to verify the performance of MOCMCSO. In the simulation, the two-dimensional grid environment is built on the basis of actual data center equipment room, the path planning and navigation are carried out by the intelligent patrol car to determine the effect of the APFM and MOCMCSO cooptimization algorithm in terms of shortest path length and optimum path smoothness.

The experiment is conducted by Matlab on PC, and the computer configuration is Core i7 CPU (3.8 GHz), 16 GB RAM, and Win10 system. The area of two-dimensional grid map is set as 100*100, the starting point is (0.0), and the target point is (99,99), so as to realize the simulation for the actual environment. The path planning algorithm is affected by the path points *i*, too many path points will lead to the global path length redundancy and larger total turning-angle variation, too few path points will lead to the collision risk. Therefore, a reasonable value selection on *i* in the experiment is necessary.

A. SOFTWARE SYSTEM

The ROS integrates a variety of practical tools, libraries and protocols, which greatly reduces the difficulty of complex task creation and movement control based on robot platform, and can support developers to quickly implement task creation, programming and control for robot applications, so the ROS is selected to build the software system of intelligent patrol car in this paper. The main functions of ROS include that abstract description for hardware device in robot, management for bottom-level drivers, execution of common functions, messages transmission among system function modules, published applications management

 TABLE 3. MOCMCSO algorithm initialization parameter.

Parameters	Value
Initial cats	50
i (cats dimension)	32
SMP	3
SRD	0.05
CDC	80%
MR _{max}	0.95
MR _{min}	0.15
w	0.1-0.9
С	2
r	[0,1]
ε	0.01
С	[0,1]
IT _{max}	100

and visualization tools, and so on. The software system of intelligent patrol car is designed mainly based on the ROS navigation package. The path planning function package outputs two types of messages (angular velocity w and linear velocity v) to the driving function package. These messages are subscribed by the bottom driver and converted to the speed of the left and right wheels. The motor drives the intelligent patrol car to move or avoid obstacles controls with PID algorithm.

This paper focuses on the novel global path planning method of intelligent patrol car. The driving patrol car is realized by using the navigation package by registering the novel path planning algorithm proposed in this paper to the BaseGlobalPlanner module in ROS. The optimized global path by the algorithms of MOCMCSO, MOCSO and MOPSO is written into the navigation module of intelligent patrol car to drive it to move. In addition, the 3D visualization tool RVIZ (ROS visualization tool) is selected as the human-computer interaction tool to conduct real-time observation and control for patrol car, which can display the map constructed by the function of simultaneous localization and mapping (SLAM), and identify the position, heading, planned path and obstacle avoidance situation in real time.

B. SELECTION OF PATH POINTS

In order to verify the effect of path planning with different values on *i*, the optimization method of APFM+CMCSO (single object optimization version of MOCMCSO) is used to carry out the path planning simulation, and the collaborative optimization method on the CSO and PSO with APFM are introduced to compare with the APFM+CMCSO. The initialization parameters of the three algorithms are shown in TABLE 3. The population number is 50, the maximum number of iterations is 100, and the dimension of cats is the path point existing in a global path. In order to simplify the experimental process, two types of independent optimization

tests on single objective function are carried out to find the optimal value on *i*.

Each algorithm achieves the independent simulation experiment ten times to calculate the average value of the global path length and the total turning-angle variation, where the change range of path point *i* is 20 to 40, and the interval of each value change is 4 path points. In the two-dimensional grid environment, obstacle avoidance and global path optimization are carried out, the effect of path planning with different value of *i* is shown in Fig. 4. It can be seen that the path planning effect of the three algorithms are all affected by path point *i*, among which, the global path length of the three algorithms obtain the minimum when path point i = 32. Besides, the total turning-angle variation is relatively low, and the path smoothness can be guaranteed simultaneously. When the value of *i* continues to increase, the path planning length and total turning-angle variation gradually increase, thus, the path smoothness is affected. This is because the larger the path point i is, the higher the dimension of the cats to be calculated is, and computational complexity is also greatly increased, resulting in slower convergence speed as a whole. In this situation, the patrol car fails to obtain the optimal solution within the specified calculation time for real-time response, and the increase of path points will also increase the additional turning-angle variation, which will affect the movement efficiency.

As can be seen from Fig. 4(a), the global path length planned by CMCSO is shorter than that of CSO and PSO. When i = 32, the average length of global path is the shortest, that of CMCSO is 35.87 m, which is better than 39.05 m of CSO and 48.57 m of PSO. When the path point *i* is 20, 24, 28 or 36, 40, the global path length gradually becomes longer. This is because when the path points are too few, the patrol car prefers the grid area with less obstacles to avoid overlapping with the obstacle coordinates in different line segments of the global path, and the broken line created by the redundant path points also violates the principle of the shortest straightline distance between the starting point and the target point, resulting in the increase of the global path length. It can be seen from Fig. 4(b) that when i is 20, 24, the total turningangle variation of the three algorithms is relatively low, but increases rapidly when *i* is greater than 28. At the point of i = 32, the total turning-angle variation of APFM+CMCSO reaches the minimum value 4.5 rad $(1 \text{ rad}=57.3^{\circ})$, which is better than 5.04 rad of CSO and 5.68rad of PSO. Then, the value of total turning-angle variation continues to increase significantly with the increase of *i*. According to the simulation results, the path line segments are straighter in the case of fewer path points and the total turning-angle variation is low, which is also easy to produce collision in a complex obstacle environment. In the case of more path points, the increase of path points can expand the global optimization range, guaranteeing that the algorithm can select the grid far away from the obstacles. Meanwhile it will increase the number of corners, resulting in the increase of total turning-angle variation and insufficient path smoothness.



FIGURE 4. Tendency to change with the number of path point *i*.

Therefore, the value of path point *i* will definitely affect the path planning results, including the path length, smoothness and security. The APFM+CMCSO algorithm performs better than APFM+CSO and APFM+PSO in the global path planning of indoor environment for the intelligent patrol car, the global path is shorter and the total turning-angle variation is lower, the optimal value of path point *i* in this experimental environment is 32.

C. MULTI-OBJECTIVE OPTIMIZATION

In this section, the multi-objective optimization experiment is carried out to verify that the APFM+MOCMCSO algorithm can ensure the global path length is shorter and the total turning-angle variation is lower simultaneously. Firstly, the initial global path can be obtained by APFM, which is the initial position of the cats. Then, MOCMCSO is executed for global optimal solution, in which, the objective function of multi-objective optimization model is (18), $f_1(x)$ and $f_2(x)$ represent the global path length and the total turning-angle variation respectively, both of the objective functions require the minimum value, and the path safety is controlled by the repulsion potential field generated by APFM in each grid to ensure the safe distance between patrol car and obstacles. The global optimal solution is set as the midpoint with 50% weight of each objective function in Pareto curve. The

TABLE 4.	Fitness value and optimization time on global optimal solution
obtained b	y MOCMCSO, MOCSO and MOPSO with APFM.

Para meter	APFM+MOCMCSO		APFM+1	MOCSO	APFM+MOPSO		
	Optimal value	Mean value	Optimal value	Mean value	Optimal value	Mean value	
$\begin{array}{c} \text{Min} \\ f_1 \\ \text{(m)} \end{array}$	31.98	35.87	34.42	39.06	39.45	48.57	
$\begin{array}{c} \text{Min} \\ f_2 \\ \text{(rad)} \end{array}$	4.12	4.50	4.81	5.69	6.37	7.89	
Time (s)	1.1885	1.5392	1.9362	2.4655	2.0452	2.1804	

MOCSO and MOPSO are used to compare the optimization effect with MOCMCSO, each algorithm performs 20 rounds of experiments independently, and output the optimal value and mean value.

It can be seen from Fig. 5 that the optimal solutions of the three algorithms with APFM are all uniformly distributed on the effective surface of Pareto curves, and the multi-objective optimization effect of the three algorithms are relatively excellent. Among them, the Pareto curve of MOCMCSO is the clearest and most complete, and the optimization effect for the two objective functions is relatively more balanced compared with MOCSO and MOPSO, achieving the goal of the shortest global path and the minimum total turning-angle variation with 1:1 ratio on (21). The Pareto curve of MOCSO is more concentrated in the lower part of the graph, and the optimization result is more affected by the global path length. Although the MOCSO can ensure the global path is shorter, it may reduce the safety and smoothness of the path due to the larger turning-angle variation and the too close distance between the patrol car and the obstacles. Meanwhile, the optimal solution is very sparse at both ends of the Pareto curve of MOPSO, mainly concentrated in the middle part, the curve is not smooth and evenly distributed, and the optimization effect at both ends is not good, so the global optimization ability of MOPSO is insufficient.

The values of optimal solution and average optimization time of the three algorithms are shown in TABLE 4. Because the Cauchy mutation operator is introduced to increase the population diversity and avoid falling into the local optimum, the average time on multi-objective problem in APFM+MOCMCSO is the shortest, which is only 1.5392 s, while the average optimization time of MOCSO and MOPSO is 2.4655 s and 2.1804 s, ensuring that the intelligent patrol car can accept control command and respond quickly in complex indoor environment.

The global optimal path comparison for MOCMCSO, MOCSO and MOPSO in the grid map for real environment simulation is shown in Fig. 6. The MOCMCSO not only has





FIGURE 5. Multi-objective optimization effect of three algorithms with APFM.

the shortest global path length, but also takes into account the lower total turning-angle variation, and its curve smoothness is the best because it avoids large-angle turns in adjacent grids. Then, the global path length of MOCSO is slightly



FIGURE 6. Comparison for global optimal paths obtained by MOCMCSO, MOCSO and MOPSO with APFM.

longer compared with that of MOCMCSO, the algorithm selects a grid relatively far away from the obstacles to ensure the safety in the 14th-18th segment shown in Fig. 6, resulting in a significant increase in total turning-angle variation, and the global optimization effect is slightly worse. Besides, the MOPSO chooses the path with longer global length and more broken lines for obstacle avoidance, which does not converge to the global optimal solution, this is because too many obstacles exist in 10th-20th segments, leading to grid selection falling into the local optimal solution for MOPSO. Therefore, the APFM+MOCMCSO takes shortest time in terms of global path optimization compared with the APFM+MOCSO and APFM+MOPSO, and the optimal value of global path length and total turning-angle variation are lowest (31.98 m, 4.12 rad). In addition, the Pareto curve of APFM+ MOCMCSO is also more complete, the Pareto optimal solution distribution is more balanced, and a good balance is achieved in terms of path planning efficiency, path smoothness and path safety, so it is most suitable for solving the multi-objective problem on global path planning of intelligent patrol car in complex indoor environment.

IV. EXPERIMENT AND ANALYSIS

The experiment system of patrol car for inspection has been built, and the global path optimization experiment is carried out in the indoor power distribution equipment room.

A. HARDWARE PLATFORM

The hardware platform of patrol car built in this paper is mainly a two-wheeled difference driven control mobile robot (EAI smart model) based on ROS. As shown in Fig. 7, the platform integrates various intelligent devices, including visible/thermal imaging camera, laser radar, obstacle avoidance sensor, inertial measurement unit (IMU), mobile supercomputing platform, industrial personal computer (IPC),



FIGURE 7. Hardware platform of patrol car built with two-wheeled difference driven control.



FIGURE 8. Control control system flow chart of intelligent patrol car.

wireless customer premise equipment (CPE), drive controller, and brushless DC hub-motor, and so on. The platform is divided into three layers. The bottom layer is equipped with drive wheel, universal wheel and motor, the middle layer includes power board, navigation board, chassis control board, laser radar and supercomputing platform, and the upper layer is equipped with camera, smoke sensor and display device.

--Dahua BF2221, a thermal imaging camera with temperature measurement, is a video acquisition device for defect detection for industrial equipment, which grabs the equipment images in two modes of visible and thermal imaging, and transmits them to the cloud computing center for processing based on computer vision models through wireless network.

--The navigation board (host computer) adopts the embedded industrial computer (Intel i5 processor, 16GB memory, 256G SSD solid-state disk), and the ROS operating system is installed. --The control processor (embedded data processing board) adopts Arduino Mega 2560, which receives the navigation information from host computer and drives motor.

--The sensor unit includes a driving wheel odometer and two four thread lidars (EAI G4 model) on the underside and top of the platform chassis, and an ADI16488 of six-axis inertial sensor located in the patrol car.

The control board is connected with the navigation board through USB-B interface to control the position, speed and torque mode of the patrol car. The lidar is connected to the navigation board through USB interface, and the scanned environmental information is fed back in real-time to avoid obstacles. In addition, the experimental platform adopts embedded supercomputing platform (MYNT CUBE) to run various deep-learning models to process the video data obtained by HD camera and conduct computer vision model training. The operating system of control board is Ubuntu 16.04, with OpenCV 3.4 [21] and TensorFlow 1.6 [22] installed.

The hardware structure of intelligent patrol car for data acquisition and driven control is shown in Fig 7. The Hi-Definition video is processed with MYNT CUBE to realize object recognition and defect detection. The navigation data calculation and central control are carried out with IPC in the mobile robot platform. The navigation information is sent to the control board and is transformed into angular speed and linear speed so as to drive the patrol car to move. Then, the control board receives the pulse data of driver to calculates the real-time motion information, and returns the results to IPC to obtain real-time posture of patrol car.

B. CONTROL SYSTEM

The control system flow chart of intelligent patrol car is shown in Fig 8. The whole platform can be divided into three parts: environment sensing control part, data processing control part and network communication control part.

--The environmental sensing control part includes a series of sensors, such as thermal imaging camera, visible light high-definition camera, smoke sensor for patrol car inspection, and lidar, posture sensor and pulse encoder for location and navigation.

--The data processing control part is the operation and control unit of patrol car, including IPC, embedded data processing board, drive board, brushless DC hub-motor, communication module, etc. The embedded data processing board can collect data from multiple sensors for data measurement and data fusion to control the drive board and DC hub-motor, and can also communicate with cloud computing server cluster. IPC is the core of the whole platform, which provides a series of functions, such as positioning, navigation, path planning, etc., to achieve reliable movement and inspection.

--The network communication control part realizes the data exchange function between the intelligent patrol car and the control center. The intelligent patrol car transmits internal data and receives external data through wireless gateway and antenna. The intelligent devices in the platform can realize reliable communication through LAN, and communicate with cloud computing server cluster through 5G network, the thermal imaging data of power distribution equipment, image data of instruments and meters, status and posture of patrol car, and fault data of the system can be uploaded to the control center. The platform receive the control data and inspection task data sent by the control center to realize routine and specific inspection task.

The control software of intelligent patrol car is used to integrate the core algorithms on environment modeling, positioning, path planning and navigation to perform inspection task.

C. GLOBAL PATH PLANNING EXPERIMENT

The EAI-smart intelligent patrol car is selected as hardware platform for experiment, and is controlled by management software deployed in PC in the same WLAN, the PC and patrol car are installed with Ubuntu 16.04 and ROS indigo system of the same version. The management software drives



FIGURE 9. Comparison for global optimal paths obtained by several algorithms by experiment in the indoor equipment room.

patrol car movement by calling ROS navigation module and communicating with chassis, and the experiment environment and movement path can be observed by RVIZ software.

In the process of path following, the intelligent patrol car adopts Adaptive Monte Carlo localization (AMCL) algorithm to locate its own position based on the generated grid map information. The motion model and sensing model of the patrol car are brought into the particle filter to solve the approximate probability distribution of the posture of patrol



FIGURE 10. The optimal inspection path obtained by the APFM+MOCMCSO and actual inspection images on the intelligent patrol car in the indoor equipment room.

car. The location module on AMCL subscribes the coordinate transformation data published by lidar driver and data processing module, and map information published by grid map management module, so the coordinate transformation from "map" to "coordinate system" of lidar can be calculated. According to the TF transform tree in ROS, the specific location information of the patrol car can be obtained.

The experimental environment is the data center room in a large electrical manufacturing enterprise, with an area of 20 m*20 m=400 m², including 48 sets of electrical, power and communication equipment such as servers, distribution cabinets, and so on. In the navigation process of intelligent patrol car, the obstacles in the experimental environment are identified by multi-threaded LIDAR, so as to plan the best path to reach the target point. The map information of patrol car is obtained based on the SLAM function, the navigation module receives the path information planned by APFM+MOCMCSO to drive the chassis to move. The resolution ratio of grid is 0.5 m, the maximum linear speed of patrol car is set as 0.6 m/s, and the maximum angular speed is 0.4 rad/s.

The map created by SLAM is shown in Fig. 9, the environment of indoor equipment room is transformed into a cost map, the gray area in the map represents obstacles, i.e. all kinds of servers, power cabinets, distribution cabinets, network switches, and concrete pillars. The black wrapped area outside the obstacles represents the obstacle range of the opened door in an electrical or communication equipment due to heat dissipation. According to the turning radius of patrol car, it is necessary to ensure no collision after expansion, the collision threshold for the obstacle is set as 20 cm based on practical experience. Meanwhile, the white area is a safe area and the patrol car can move freely.

In order to verify the simulation results in TABLE 4. The path planning experiment of intelligent patrol car based on APFM+MOCMCSO is carried out. The APFM+ MOCSO and APFM+MOPSO are introduced for comparison. In addition, the A*, the most widely used heuristic search algorithm, is also introduced as an object of comparison in experiments. The intelligent patrol car constructed in this paper carries out 40 rounds of navigation experiments in the indoor equipment room, the APFM+MOCMCSO, APFM+MOCSO, APFM+MOCSO, APFM+MOPSO and A*algorithm are used to find the optimal path, and each algorithm is run 10 times. The global path length, total turning-angle variation, total motion time and collision times recorded in the experiment is shown in TABLE 5. The global optimal paths obtained by APFM+MOCMCSO, APFM+MOCSO, APFM+MOCSO,

APFM+MOCMCSO			APFM+MOCSO		APFM+MOPSO			A* algorithm				
Experiment number	Global path length (m)	Turning- angle variation (rad)	Total time(s)	Global path length (m)	Turning- angle variation (rad)	Total time(s)	Global path length (m)	Turning- angle variation (rad)	Total time(s)	Globa l path length (m)	Turning- angle variation (rad)	Total time(s)
The 1st	37.62	10.93	113.2	40.89	12.35	144.6	42.50	11.97	176.2	47.82	12.08	189.0
The 2nd	38.83	9.12	107.1	41.63	12.88	137.2	44.12	13.05	161.9	46.58	12.24	188.4
The 3rd	40.05	9.79	135.5	39.01	9.27	146.8	47.86	14.99	189.0	50.95	14.17	205.7
The 4th	36.52	8.37	98.8	45.70	15.61	152.9	47.77	13.37	178.3	50.17	13.75	211.4
The 5th	38.03	9.25	120.5	41.18	13.02	150.2	43.24	11.23	156.8	44.93	11.72	180.2
The 6th	37.58	10.07	130.0	39.98	14.68	138.2	40.50	9.97	147.2	47.34	11.90	192.9
The 7th	38.75	10.52	148.6	44.59	15.34	165.8	43.19	12.01	158.6	49.92	12.58	195.7
The 8th	39.47	9.36	132.9	49.62	17.19	147.4	49.82	15.28	196.8	52.25	14.76	218.6
The 9th	40.28	13.44	156.8	44.37	14.86	136.9	47.71	12.86	165.5	48.77	12.99	203.3
The 10th	36.94	8.83	104.1	48.54	15.50	146.1	49.11	12.75	167.3	45.21	13.50	183.4
Mean value	38.41	9.97	124.8	43.55	14.07	146.6	45.58	12.75	169.8	48.39	12.97	196.9
Optimal value	36.52	8.37	98.8	39.01	9.27	146.8	40.50	9.97	147.2	44.93	11.72	180.2

TABLE 5. Experimental results on path planning based on APFM+MOCMCSO, APFM+MOCSO, APFM+MOPSO and A* algorithm.

APFM+MOPSO and A*algorithm is shown in Fig. 9. The optimal path obtained by APFM+ MOCMCSO in the 4th experiments is 36.52 m in global path length and 8.37 rad in total turning-angle variation, which are both the minimum in 10 results, ensuring the highest movement efficiency for the patrol car while taking into account the global path smoothness, and there is no obstacle collision in the whole movement process. Based on the APFM+MOCMCSO algorithm, the total movement time of the patrol car from the starting point to the target point is 98.8s, which can meet the efficiency requirements for automatic inspection in the 400 m² equipment room.

The optimal path obtained by APFM+MOCSO is 39.01 m in global path length and 9.27 rad in total turning-angle variation, that of APFM+MOPSO is 40.5 m and 9.97 rad. Moreover, the mean values of the three algorithms are calculated through 10 experiments respectively. Compared with the APFM+MOCSO and APFM+MOPSO, APFM+MOCMCSO algorithm has a shortest global path length (38.41 m) and a minimum total turning-angle variation (9.97 rad). In the process of global navigation, the mean value of total movement time of APFM+MOCMCSO is the minimal (124.8 s) in the algorithms, so the APFM+ MOCMCSO has maximum efficiency on path planning process. As a classic heuristic search algorithm, A*algorithm is also applied to this experiment for comparison. It can be seen that the mean value of global path length, total turning-angle

variation and total time of A* algorithm is relatively poor compared with APFM+MOCMCSO, APFM+MOCSO and APFM+MOPSO, and the value is only 48.39 m, 12.97 rad and 196.9 s. The reason for this phenomenon is that, A^{*}algorithm has too much meaningless search paths in the global search process, which is inefficient, and the planned path fails to reach global optimum, the mean value of total time is also too long. In addition, it can be seen from Fig. 9 that the optimal path obtained by APFM+MOCSO ensures the shortest path between the starting point and the target point. Compared with the other three algorithms, the optimal path is shorter and smoother, in particular, the turning-angle variation between the adjacent lines is the smallest, so the patrol car will not reduce the movement efficiency and avoid collision with obstacles. On the whole, for the experiment based on the navigation module in the intelligent patrol car, the APFM+MOCMCSO algorithm proposed in this paper has the shortest global path length, the minimum total turning-angle variation, and the minimum total movement time. The effect of APFM+MOCMCSO is better than that of APFM+MOCSO, APFM+MOPSO and A* algorithms in terms of global path planning, and is more suitable for the path planning task on intelligent patrol car in the indoor environment.

In the navigation process, the image of the patrol car at 12 important path points is shown in Fig. 10, proving that the patrol car can complete the inspection task without making

collisions in the indoor environment. The path planning by APFM+MOCMCSO has a high degree of compliance in simulation and experiment. The optimal global path length is similar, which is 31.98 m of simulation and 36.52 m of experiment, but the experimental value (8.37 rad) is much larger than the simulation value (4.12 rad) on total turningangle variation. The space of indoor equipment room is narrow, and the distance between equipment is very close. Some equipment doors must be kept open due to heat dissipation, the expansion radius of this obstacles is enlarged. The patrol car often triggers emergency braking during operation and adjusts direction to avoid obstacles based on the guidance of ultrasonic sensors. Therefore, it is inevitable that the turningangle variation between adjacent path segments is significantly greater than the ideal simulation results.

In the 10 rounds of experiment on APFM+MOCMCSO, there is only one obstacle collision in the 9th experiment, the patrol car is too close to the obstacle. It triggers the emergency brake on ultrasonic sensor, and need to adjust the position, posture and path several times for coordinate correction, resulting in the total turning-angle variation increases to 13.44 rad, and the total movement time increases up to 156.8 s. Therefore, the algorithm needs to take the emergency braking factors of ultrasonic sensor into account to avoid the influence of too close obstacle avoidance distance.

V. CONCLUSION AND FUTURE WORK

This paper mainly studied the global path planning algorithm of intelligent patrol car in the indoor scene of data center equipment room. According to the two-dimensional grid mapping of known operating environment, a collisionfree optimal path is planned from the starting point to the target point. The evaluation criteria includes the shortest total length, the best path smoothness, and safety. A co-optimization method on the APFM and MOCMCSO are presented, the path generated by APFM is set as initial position of cats in MOCMCSO algorithm. The global path length and total turning-angle variation are set as two objective functions. The optimal path obtained by the APFM+MOCMCSO is written into the navigation module to drive the patrol car to move quickly. The solution of the Pareto curve with equal weight of two objective functions is taken as the global optimal solution. According to the simulation results, the APFM+MOCMCSO has faster searching speed, shorter optimization time, lower fitness value, better balance between multiple objective functions compared with APFM+MOCSO and APFM+MOPSO, and is more suitable for path planning of intelligent patrol car in complex indoor environment. Finally, an actual navigation experiment is carried out in the data center equipment room (400 m^2) of a large electrical manufacturing enterprise. The global path length optimized by APFM+MOCMCSO algorithm is only 36.82 m, and the total turning-angle variation is 5.33 rad. It apparently improves the effectiveness, stability and accuracy of the APFM+ MOCMCSO in the complex indoor equipment room, and the optimal path can be obtained in the shortest time. The proposed algorithm will be used in various inspection scenes of intelligent patrol car.

Through the analysis on the experimental results, the performance of path planning on APFM+MOCMCSO algorithm for intelligent patrol car will be continuously improved in the following two aspects:

- 1) The environment for obstacle avoidance and navigation in indoor equipment room is very complex, sometimes, the patrol car needs to go deep into the narrow access to cabinets for sudden patrol tasks. It is difficult for patrol cars to ensure that the global path is beyond the safe distance (20 cm) of anti-collision. Therefore, in addition to the shortest path and the minimum total turning-angle variation, it is necessary to increase anticollision security optimization strategy based on the repulsion of the potential field to ensure that the patrol car can plan a particular path even in extremely narrow spaces.
- 2) In the inspection scene of the equipment room, patrol car is required to detect the equipment in the way of daily operation. In the inspection process, it may occur that the same path points are repeatedly reciprocating in one operation. In the case of multiple target points, the path planning algorithm needs to solve the problems of shortest overall path length, minimum movement time and highest efficiency in the reciprocating motion of the same path points.

REFERENCES

- Y. Tian, T.-M. Choi, X. Ding, R. Xing, and J. Zhao, "A grid cumulative probability localization-based industrial risk monitoring system," *IEEE Trans. Autom. Sci. Eng.*, vol. 16, no. 2, pp. 557–569, Apr. 2019.
- [2] S. M. Rathod and S. K. Apte, "Obstacle detection using sensor based system for an four wheeled autonomous electric robot," in *Proc. Int. Conf. Commun. Electron. Syst. (ICCES)*, Coimbatore, India, Jul. 2019, pp. 493–497.
- [3] R. S. Lim, H. M. La, and W. Sheng, "A robotic crack inspection and mapping system for bridge deck maintenance," *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 2, pp. 367–378, Apr. 2014.
- [4] S. Zhang, S. Wang, F. Jing, and M. Tan, "A sensorless hand guiding scheme based on model identification and control for industrial robot," *IEEE Trans. Ind. Informat.*, vol. 15, no. 9, pp. 5204–5213, Sep. 2019.
- [5] S. Saeedi, L. Paull, M. Trentini, and H. Li, "Neural network-based multiple robot simultaneous localization and mapping," *IEEE Trans. Neural Netw.*, vol. 22, no. 12, pp. 2376–2387, Dec. 2011.
- [6] M. Garcia Puyol, D. Bobkov, P. Robertson, and T. Jost, "Pedestrian simultaneous localization and mapping in multistory buildings using inertial sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1714–1727, Aug. 2014.
- [7] C. Guo, D. Li, G. Zhang, and M. Zhai, "Real-time path planning in urban area via VANET-assisted traffic information sharing," *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 5635–5649, Jul. 2018.
- [8] G. Diaz-Arango, H. Vazquez-Leal, L. Hernandez-Martinez, M. T. S. Pascual, and M. Sandoval-Hernandez, "Homotopy path planning for terrestrial robots using spherical algorithm," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 2, pp. 567–585, Apr. 2018.
- [9] D. Hu, Y. Gong, B. Hannaford, and E. J. Seibel, "Path planning for semi-automated simulated robotic neurosurgery," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Hamburg, Germany, Sep. 2015, pp. 2639–2645.
- [10] T. Nageli, J. Alonso-Mora, A. Domahidi, D. Rus, and O. Hilliges, "Realtime motion planning for aerial videography with dynamic obstacle avoidance and viewpoint optimization," *IEEE Robot. Autom. Lett.*, vol. 2, no. 3, pp. 1696–1703, Jul. 2017.

- [11] S. Wang, J. Zhang, and J. Zhang, "Artificial potential field algorithm for path control of unmanned ground vehicles formation in highway," *Electron. Lett.*, vol. 54, no. 20, pp. 1166–1168, Oct. 2018.
- [12] G. Narvydas, R. Simutis, and V. Raudonis, "Autonomous mobile robot control using fuzzy logic and genetic algorithm," in *Proc. 4th IEEE Workshop Intell. Data Acquisition Adv. Comput. Syst., Technol. Appl.,* Dortmund, Germany, Sep. 2007, pp. 460–464.
 [13] R. Kala, A. Shukla, and R. Tiwari, "Fusion of probabilistic A* algorithm
- [13] R. Kala, A. Shukla, and R. Tiwari, "Fusion of probabilistic A* algorithm and fuzzy inference system for robotic path planning," *Artif. Intell. Rev.*, vol. 33, no. 4, pp. 307–327, Apr. 2010.
- [14] T. J. Chen, Y. Sun, W. Dai, W. Tao, and S. Liu, "On the shortest and conflict-free path planning of multi-AGV system based on dijkstra algorithm and the dynamic time-window method," *Adv. Mater. Res.*, vol. 645, pp. 267–271, Jan. 2013.
- [15] H. Sun, "Path-based Floyd algorithm in automatic search system," Lect. Notes Electr. Eng., vol. 219, no. 10, pp. 531–537, Jun. 2013.
- [16] X. Zhong, J. Tian, and H. Hu, "Hybrid path planning based on safe A* algorithm and adaptive window approach for mobile robot in large-scale dynamic environment," *J. Intell. Robotic Syst.*, vol. 107, no. 8, pp. 65–77, Jan. 2020.
- [17] P. Xu, "Research on optimized model of travel route selection based on intelligent image information and ant colony algorithm," *Multimedia Tools Appl.*, vol. 2019, no. 8, pp. 1–17, Apr. 2019.
- [18] P. K. Das, H. S. Behera, P. K. Jena, and B. K. Panigrahi, "Multi-robot path planning in a dynamic environment using improved gravitational search algorithm," *J. Electr. Syst. Inf. Technol.*, vol. 3, no. 2, pp. 295–313, Sep. 2016.
- [19] W. Zhang, Y. Ma, and H. D. Zhao, "Obstacle avoidance path planning of intelligent mobile based on improved fireworks-ant colony hybrid algorithm," *Control Decis.*, vol. 34, no. 2, pp. 335–343, Nov. 2019.
- [20] S. M. Zadeh, A. M. Yazdani, and K. Sammut, "AUV rendezvous Online path planning in a highly cluttered undersea environment using evolutionary algorithms," *Appl. Soft Comput.*, vol. 24, no. 12, pp. 70–79, Apr. 2016.
 [21] G. Bradski, "The opencv library," *Dr Dobb's J. Softw. Tools*, vol. 25,
- [21] G. Bradski, "The opencv library," Dr Dobb's J. Softw. Tools, vol. 25, pp. 120–126, 2000.
- [22] M. Abadi et al. (2015). TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. [Online]. Available: http://tensorflow.org/
- [23] Y. Lu, S. Yi, Y. Liu, and Y. Ji, "A novel path planning method for biomimetic robot based on deep learning," *Assem. Autom.*, vol. 36, no. 2, pp. 186–191, Apr. 2016.
- [24] H. Hong-Gui, L. U. Wei, and Q. Jun-Fei, "A multiobjective particle swarm optimization algorithm based on the diversity information and convergence degree," *Acta electronica sinica*, vol. 46, no. 2, pp. 315–324, Feb. 2018.
- [25] M. Pandi, R. Balamurugan, and N. Sadhasivam, "Cancer detection in microarray data using a modified cat swarm optimization clustering approach," *Asian Pacific J. Cancer Prevention*, vol. 18, no. 12, pp. 3451–3455, Dec. 2017.
- [26] B. Crawford, R. Soto, and N. Berríos, "A binary cat swarm optimization algorithm for the non-unicost set covering problem," *Math. Problems Eng.*, vol. 10, no. 1, pp. 1–9, Aug. 2015.
- [27] B. Kumar, M. Kalra, and P. Singh, "Discrete binary cat swarm optimization for scheduling workflow applications in cloud systems," in *Proc. 3rd Int. Conf. Comput. Intell. Commun. Technol. (CICT)*, Ghaziabad, India, Feb. 2017, pp. 1–6.
- [28] S. Temel, N. Unaldi, and O. Kaynak, "On deployment of wireless sensors on 3-D terrains to maximize sensing coverage by utilizing cat swarm optimization with wavelet transform," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 44, no. 1, pp. 111–120, Jan. 2014.
- [29] G. Ram, D. Mandal, R. Kar, and S. P. Ghoshal, "Cat swarm optimization as applied to time-modulated concentric circular antenna array: Analysis and comparison with other stochastic optimization methods," *IEEE Trans. Antennas Propag.*, vol. 63, no. 9, pp. 4180–4183, Sep. 2015.
- [30] P. K. H. Kulkarni and P. Malathi Jesudason, "Multipath data transmission in WSN using exponential cat swarm and fuzzy optimisation," *IET Commun.*, vol. 13, no. 11, pp. 1685–1695, Jul. 2019.
- [31] D. Yan, H. Cao, Y. Yu, Y. Wang, and X. Yu, "Single-Objective/Multiobjective cat swarm optimization clustering analysis for data partition," *IEEE Trans. Autom. Sci. Eng. (from July 2004)*, vol. 17, no. 3, pp. 1633–1646, Jul. 2020.
- [32] L. Pappula and D. Ghosh, "Synthesis of linear aperiodic array using cauchy mutated cat swarm optimization," *AEU - Int. J. Electron. Commun.*, vol. 72, pp. 52–64, Feb. 2017.
- [33] D. Zhao, K. Xia, H. Liu, and X. Shi, "A pitch distribution in slowwave structure of STWT using cauchy mutated cat swarm optimization with gravitational search operator," *J. Chin. Inst. Eng.*, vol. 41, no. 4, pp. 297–307, Jun. 2018.



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